## Identifying areas of a map that are difficult to read

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**Abstract:** The aim of this paper is to develop and evaluate methods to analytically identify areas of a map that are difficult to read. The approach is to compare such areas that were found in user tests with two analytical methods: the *threshold method* and the *cluster method*. These methods are implemented and evaluation shows that both methods have the potential of identifying areas that are difficult to read. A main advantage with the cluster method is that it is computationally more efficient than the threshold method, which makes it the best candidate for integration in a real-time service. The cluster method, or similar, could in the future be used as a guidance in the generalization process to improve map legibility in e.g. web services.

Keywords: cartography, map legibility, web services, map reading, expert user tests, clustering.

## 1. Introduction

The usage of maps has changed profoundly during the last decade. Today, a large portion of the maps are screen maps originating from web services. We could anticipate that this change in map use will continue in the future, especially since most countries are building up national spatial data infrastructures, which are partly based on geoportals. A change that most likely will occur is that more web based map services will distribute geospatial data rather than predefined maps. This development will provide possibilities to integrate geospatial data from several sources. However, creation of maps using geospatial data from several sources in real-time introduces new challenges; one such challenge concerns the legibility of the maps.

In automated cartography legibility is mainly studied in a bottom-up approach. By legibility constraints a program identifies features, or group of features, that are regarded as non-legible (e.g. overlapping or too close features). Then generalization algorithms are applied to resolve these non-legibility problems. The aim of this study is somewhat different. Instead of studying isolated violations of the legibility rules (constraints) we aim at identifying areas in a map that a map reader perceives as difficult to read. The rationality behind this approach is that a map reader may accept isolated violations of the legibility rules, at least in a real-time map, but he/she cannot accept areas of the map that are not readable. Therefore, it would be interesting to establish analytical methods for identifying the areas that are hard to read. The real-time generalization should then mainly focus on resolving conflicts in these areas. This approach inevitably leads to maps where generalization is performed solely on areas that are identified as hard to read; in other words, the type and level of generalization applied is not the same for all parts of the map. This situation may be undesired; however, in real-time generalization of

maps viewed in a geoportal time efficiency and readability can be considered as more important than an evenly generalized map.

## 2. Related work

Identifying areas that are difficult to read in a map is linked to the presence of clutter. It has been shown that clutter has a negative effect on the performance and likeability of visual presentations (Phillips and Noyes, 1982). In cartography the removal of clutter is performed by generalization. However, one problem in this aspect is to know when a map is too cluttered and in need of generalization. To perform this we need measures of clutter and also an evaluation strategy of the effect of generalisation. One example of the latter is given by Jansen and van Kreveld (1998). A grid is placed on a map and a clutter function is applied to quantify the amount of clutter in each grid cell. The evaluation if performed by comparing the amount of clutter for each cell before and after the generalisation.

There have been several studies for measures of clutter and quantifying the information in maps. The measures can be categorised into the following classes:

- 1) information amount, e.g. the number of objects (Phillips and Noyes, 1982; Wolfe, 1994; Oliva et al., 2004), the number of objects of a particular type (Töpfer and Pillewizer, 1966)
- 2) spatial distribution of information, e.g. distribution of objects (MacEachren, 1982), their symmetry and organization (Oliva et al., 2004), entropy measures for objects and points (Bjørke, 1996; Li and Huang, 2002),
- 3) complexity of information, e.g. sinuosity (João, 1998), total angularity (McMaster, 1987), and line connectivity (Mackaness and Mackechnie, 1999; Fairbairn, 2006).
- 4) symbology, e.g. different aspects of colours (e.g. contrast) of the visualized objects (Eley, 1987; Oliva et al., 2004), legibility of graphics (Robinson et al., 1995; Spiess 1995).

Some researchers have proposed that a single measure never can explain if an area in a map is hard to read (i.e., is cluttered) and that you have to consider synthesis of measures (Rosenholtz et al, 2005, 2007; Schnur et al., 2010; Stigmar and Harrie, 2011; Stigmar et al., 2011). However, to the authors knowledge there have not yet been any studies that are using measures to explicitly find areas in the map that are difficult to read.

## 3. Methodology

First we prepared map data (section 3.1). These map data were used to perform user studies to identify which areas in the map that are perceived as hard to read by a user (section 4). Then we developed, implemented, and tested two analytical methods for identifying these areas: the *threshold method* (section 5) and the *cluster method* (section 6). Finally, we performed an evaluation of these analytical methods with respect to the outcome of the user studies (section 7).

For the user test the map was prepared using ArcGIS from ESRI. The threshold and cluster methods were implemented in Java. *JTS Topology Suite* (JTS) (JTS, 2011) was used for geometry operations and *OpenJump* (OpenJump, 2011) for visualization.

#### 3.1 Map data

In the user test a map in the scale of 1:50 000 was used. The map was created from a geographic database from the Swedish mapping, cadastral, and land registration authority (*Lantmäteriet*) and from the local municipality of Helsingborg (*Helsingborgs kommun*).

In the case studies of the threshold and cluster methods contour lines and land cover were not included. The reason for this is that these feature types are considered as belonging to the background in the visual hierarch and should be symbolized with less distinct symbols, such as pale colours and/or thin lines. Hence, they will influence map legibility less compared to objects that are placed higher in the visual hierarchy. For example, in the urban part of the map contours are barely visible.

## 4. User Tests

Twelve test persons were participating in the test. Seven of the participants were male and five female, with an average age of 40 years. Six of the participants worked on social planning; one on detailed planning, two on regional planning, and three on both. The other six participants worked with GIS at university level. The participants' occupational experience ranged from one year to 30 years, with an average of 9 years. They worked with maps for an average of 50% of their total working time.

#### 4.1 Test Procedure

The expert test was performed individually at the participants' place of work in order to reflect their everyday working situation. The test consisted of several parts, but here we only describe the part that is of interest for this particular study. In this part the tests were performed as user evaluations where the participants were asked to give their opinions on different aspects of the map, and to mark specific problem areas. The participants were asked to do this both in a general perspective as well as with different legibility problems in mind. These legibility problems were based on the legibility measures described in Stigmar and Harrie (2011).

#### 4.2 Result

Figure 1 shows the areas in the map that were regarded as difficult to read by at least two test persons.

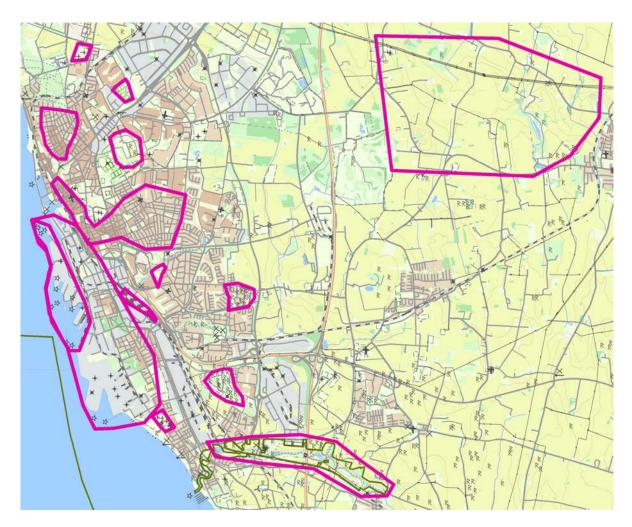


Figure 1. Areas of the map that are hard to read according to the user test. Copyright: Lantmäteriet and Helsingborgs kommun.

## 5. Threshold method

#### 5.1 Method

The threshold method is an approach to detect areas that are hard to read by using grid cells. For this, a grid is applied over the entire map where each grid cell represents a specific map region and is linked to the map's geometry. This makes it possible to carry out information measurements based on the geometry within each grid cell and to determine the information content quantitatively. A previous study on analytical estimation of map legibility by Stigmar et al. (2011) compares several information measures and provides threshold values for each measurement. The thresholds are derived from empirical tests (different to the test described

- Number of objects (<11/cm<sup>2</sup>)
- Object line length (<17cm)
- Number of vertices (<450/cm<sup>2</sup>)
- Number of object types (<17)
- Degree of overlap for disjoint objects (<3)
- Angularity (<40/cm)

The *Degree of overlap for disjoint objects* (DO) is defined as the sum of intersections between disjointed features. To ensure good legibility, an outline of 0.3 mm is adopted to the features. For this reason, a buffer is taken into account for each feature. The buffer size is based on the symbology size and a requirement of the minimum separation of 0.3 mm. The Degree of overlap is described as

$$DO = \frac{\sum_{i=1}^{n} \sum_{j=i+1}^{n} \delta_{ij} \cdot \text{Area of intersection between buffers around object } i \text{ and object } j}{\text{Area of region}}$$

where *n* is the number of objects, and  $\delta_{ij}$  is equal to 1 if object *i* and *j* are disjoint and otherwise zero.

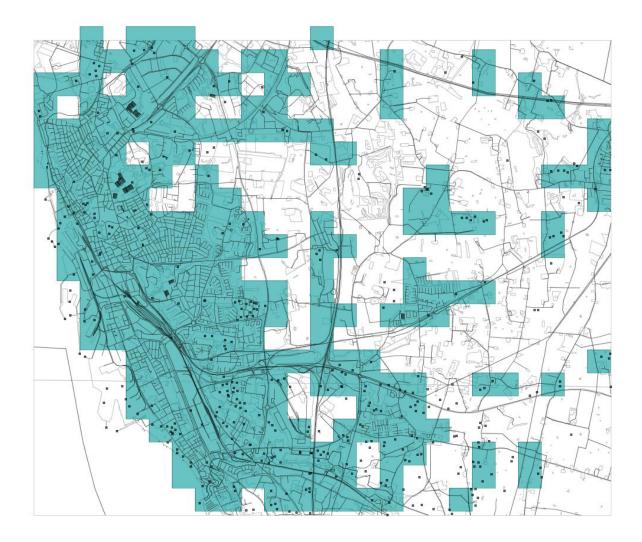
The *angularity* is defined as the sum of all the changes in direction of a line divided by its total length.

#### 5.2 Results

As described in section 5.1, most of the measured values are relative to an area unit. Therefore, the choice of cell size is crucial. In this study, a cell size of 1 cm<sup>2</sup> is used. This means illegible areas are roughly represented (Figures 2 and 3). Smaller cell sizes would state illegible areas with a higher accuracy, but leading to a higher computation time.

The algorithm is designed to determine the individual measures sequentially for each grid cell. To reach high efficiency the method starts by evaluating measures that only requires simple geometry computations (e.g. number of objects). Measures that require complex topological computations and, hence, a high running time, such as degree of overlap or angularity, are tested later. This approach is efficient in areas with high density; once a grid cell is identified as difficult to read no further measures need to be evaluated for that cell. In areas with low density the algorithm is efficient since the computations are faster due to less detail. However, for areas with medium density efficiency decreases since a high number of measures must be evaluated and these cells are richer in detail than the low density areas. To minimize object density, only data layers that present features in the fore- or middle ground

were used. Figure 2 provides the result from the threshold method using all data layers except land cover and contour lines. To shorten the computations a test was performed where also road data were left out. The result of the latter test is presented in Figure 3.



*Figure 2. Areas of the map that are hard to read as identified by the threshold method - all data types except land cover and contour lines are included.* 

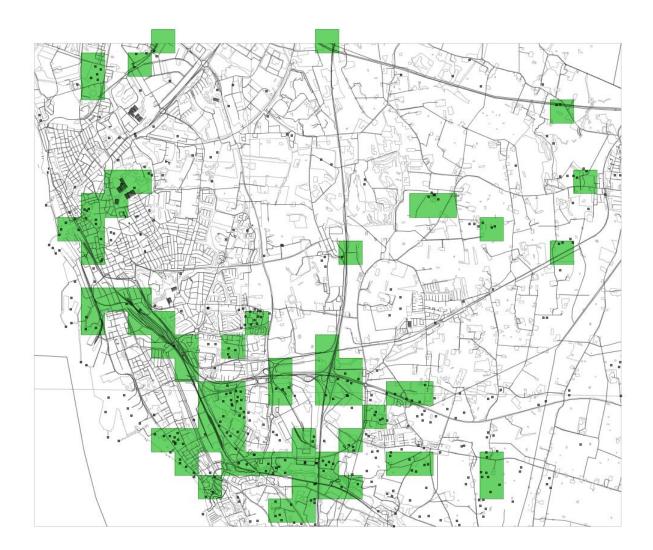


Figure 3. Areas of the map that are hard to read as identified by the threshold method - all data types except roads, land cover, and contour lines are included.

#### **5.3 Discussion**

It seems to be possible to imitate the results of the performed user tests by an automated determination of legibility based on the threshold method. The results are affected by the grid cell size, the location of each grid cell, the specific threshold values, and the data layers.

In the tests different object types have been used in the computations. When the contour lines and land cover data are included large areas of the map are identified as hard to read. The reason is that contour lines and land cover polygons are made up of a large number of points that increase the number of vertices within a grid cell. However, these points do not make the map hard to read, but they are necessary to make the lines smooth. They just affect the map reading slightly and both object types are located in the background in the printed map. It seems appropriate to exclude these data layers from an automatic analysis. At least, the measure values should be weighted according to if a feature belongs to fore-, middle, or background. Currently the grid tiles are joined together seamlessly. Depending on the location of the grid tiles, information can be lost when analyzing the legibility since the calculations refer just to each grid cell. If an area with high density of information is distributed over several tiles, thresholds may not be exceeded. A solution could be an overlap of tiles, for example 50%. Thus, every area of the map would be distributed over several tiles and areas with poor legibility would be detected. This would, however, be associated with a higher computational time.

As stated in section 5.2, the use of smaller cell sizes would identify the shapes of the illegible areas with a higher accuracy. However, due to the high computation time, we have worked with a lower grid resolution. This leads to a rough representation of the areas that are hard to read. However, since the purpose is to find the illegible areas rather than to identify their shape accurately this is acceptable.

Compared to the result of the user test much larger areas are detected as illegible by the threshold method. Currently, each measure does classify a grid cell as hard to read on its own, if this measure exceeds the threshold value. Most probably the measures affect and imply each other. In a future development of the method, constraints can be established to identify cells in the context of different measures. Some measures may classify a cell as illegible alone, while other measures only make a grid cell illegible if the threshold is exceeded also by other measure(s).

## 6. Cluster method

## 6.1 Method

The basic idea of the cluster method is to find dense clusters of *map points*. Map points are defined as the midpoint of point objects and as vertices on line and polygon objects. Clusters are then identified by applying the density based algorithm DBSCAN (Ester et al., 1996) on the map points. DBSCAN is able to find clusters of all shapes, and points that do not belong to any cluster are regarded as noise - that means that all points are not included in a cluster. In our application we are interested in finding areas where the map points are dense and form clusters there. Then the convex hulls of these clusters are regarded as areas that are difficult to read.

DBSCAN identifies an area as dense if there is a minimum number of points *minPts* within the distance  $\varepsilon$  from a point. If there are more than *minPts* points within the distance  $\varepsilon$  from a point, that point is regarded as a *core point*. Another point that is within the distance  $\varepsilon$  from a core point, but is not a core point itself, is a *border point*. Points that are not within the distance  $\varepsilon$  of any core point are regarded as noise (see Figure 4). For details about the algorithm see Ester et al. (1996) or Han et al. (2001).

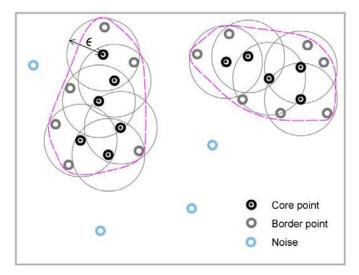


Figure 4. Two clusters identified by DBSCAN. minPts = 3.

To reach a higher correlation between the areas that are identified as difficult to read by DBSCAN and the areas perceived as hard to read in the user test, modifications of the basic idea were made.

- When a single map point is used to represent a point object, the impact of point objects on legibility is underestimated compared to the user test (Figure 1). To improve this situation a number of map points were added for each point object.

- The influence of point objects can also be increased indirectly by decreasing the impact of line and polygon objects. Especially smooth curves on lines and polygons tend to be overestimated in terms of illegibility. These gentle curves are formed by several short line segments that result in a large number of map points being created. These map points may result in clusters that are not due to poor legibility. To decrease the impact of line and polygon features the number of map points was reduced with the simplification algorithm *Douglas Peucker* (Douglas and Peucker, 1973). A threshold was defined for the ratio between line length and the number of vertices of that line to decide on which lines and polygons to apply Douglas Peucker.

- Areas with parallel straight lines, such as railway yards, are not identified as difficult to read by DBSCAN when map points are created at vertices only. Such areas are potentially difficult to read; hence, a maximum distance for line segments *maxDist* was defined. For line segments with a length exceeding *maxDist*, map points were added.

- A threshold for minimum area of the convex hulls representing the clusters was applied to omit small clusters.

#### 6.2 Result

Figures 5–6 show the areas identified by the cluster method. As shown, which areas that are identified as difficult to read is strongly affected by the parameters *minPts* and  $\varepsilon$ . In the figures the maximum length for line segments is 200 m (if longer, additional map points are added).

Large  $\varepsilon$  results in less, but larger clusters. The nature of convex hull prevents the shapes of the clusters from being clearly shown. This results in areas that are not part of a cluster, being covered by the convex hull; hence, large clusters are occasionally overlapping other clusters. With decreasing  $\varepsilon$  as in Figure 6 the number of clusters is increasing and their size decreasing, and the shapes of the convex hulls conform more to areas with poor legibility.



*Figure 5. Clusters created with minPts=7 and*  $\epsilon$ *=115m. Max length of line segments is 200 m.* 



*Figure 6. Clusters created with minPts=8 and*  $\varepsilon$ *=75m. Max length of line segments is 200 m.* 

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14th ICA/ISPRS Workshop on Generalisation and Multiple Representation, 2011, Paris Paper will be published in Mapping and Image Science (a journal of the Swedish Cartographic Society) Figure 7 and 8 shows areas that were identified as difficult to read by DBSCAN with settings as in Table 1. In Figure 7 marginally more areas that were perceived as difficult to read in the user test are identified by DBSCAN compared to Figure 8. However, Figure 7 also includes more areas that were not perceived as difficult to read.

To reduce the number of clusters a threshold was applied to remove small areas.  $250,000 \text{ m}^2$  was tested as it corresponds to  $1 \text{ cm}^2$  in scale 1:50,000. This is the unit for the thresholds defined in Stigmar and Harrie (2011) and utilized in the threshold method. However, this size of the minimum area excluded some of the areas that were identified as hard to read in the user study. Hence, a minimum area of 100,000 m<sup>2</sup> was applied.



Figure 7. Clusters created with parameter values as in Table 1.

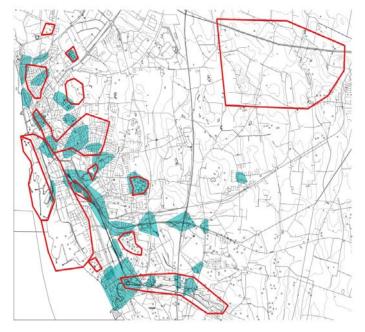


Figure 8. Clusters created with parameter values as in Table 1.

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	Figure 7	Figure 8
minPts (DBSCAN)	15	12
ε (DBSCAN)	75 m	75 m
Additional map points per point object	8	16
Ratio line length/no. of vertices (if feature should be	50 m	50 m
tolerance (Douglas Peucker)	10 m	12 m
maxDist (line segments)	50 m	100 m
Minimum area (convex hull of cluster)	100,000	100,000

Table 1. Parameter values for the cluster method to identify the clusters in Figure 7 and 8.

#### 6.3 Discussion

The main concern in Figure 7 and 8 is that line objects, mainly gently bending roads, are overestimated in terms of poor legibility; several areas that were not perceived as hard to read in the user test are identified as difficult to read by the cluster method. This situation can be improved by adjusting the parameters listed in Table 1. It is, however, so that different parameters give similar results when modified leading to a complex study.

Two important parameters are the parameters required by the DBSCAN algorithm, namely *minPts* and  $\varepsilon$ . Figure 5 and 6 clearly shows how these parameters affect the resulting clusters. However, the tests performed showed that there is no major difference between a low value for *minPts* and a high value for  $\varepsilon$ , versus a high value for *minPts* and a low value for  $\varepsilon$ .

Another concern is that the influence that point objects have on legibility is underestimated compared to the user test. The approach to add additional map points for each point object does improve the result. However, the additional computations decrease performance. An approach where the number of map points that are added for a point object is related to the symbology would be interesting to test; for simple symbols only a few map points could be added, and for complex symbols several map points. That would, however, increase the complexity of the method.

The parameters that decide when the Douglas Peucker algorithm is applied and how much the algorithm should simplify an object were also adjusted to improve the result. If a line or polygon is to be simplified is decided by the ratio between line length and the number of vertices. The tests showed that the ratio should be low to have a major effect on the result. The parameter *tolerance* (max perpendicular distance) required by the Douglas Peucker algorithm also has a major effect on the result. Naturally a high tolerance reduces the number of map points resulting in less clusters being created. However, the level of simplification must be considered so that line and polygon features are not simplified too much.

The last parameter affecting the clusters being created by cluster method is the maximum length of line segments, *maxDist*. For this parameter there is a conflicting aspect between a low value and a high value. A low value results in a large amount of map points being added and large clusters are created. A high value on the other hand leads to areas that are difficult

to read, according to the user test, not being identified.

Finally a threshold was applied on the clusters that were created by the cluster method. Minimum area for clusters naturally removes the smallest clusters; these are likely not a major problem from a legibility perspective since they are small. However, the test showed that this threshold should be kept low, otherwise the smallest areas identified as hard to read in the user test will be omitted.

In an extended future study it is likely that the result can be improved by:

- increasing the *maxDist* between map points along line segments. This would both decrease the impact of line and polygon objects and reduce the number of computations.

- increasing the *tolerance* for Douglas Peucker to decrease the impact of lines and polygons.

- adding more additional map points for each point object; this would, however, increase the number of computations.

This should be done in combination with different values for the parameters *minPts* and/or  $\varepsilon$  as required by DBSCAN

Another concern is that the convex hull is not representing the shape of large clusters (Figure 5 and 6) very well. This situation could be improved by implementing a better aggregation method of points, such as the method proposed by Joubran and Gabay (2000)

## 7. Evaluation

When the threshold and cluster methods are evaluated it should be noted that all the data used in the user test (Figure 1) are not included when the methods are tested. This means that all areas perceived as difficult to read in the user test cannot be identified by the threshold and cluster methods; these areas, which are described below, are not considered in the evaluation.

*The upper right part* – this large area was perceived as difficult to read due to the contours, which are not considered in the tests of the methods.

*The lowermost area (elongated polygon in East-West direction)* – this area is likely to be perceived as difficult to read due to a nature protection area (distinct green line with complex shape) and contours along the gully. Since the green line is a symbology problem, and contours are not included in the test of the methods, this area cannot be identified by either the threshold or the cluster method.

*The harbour area* (West) – in the dataset the coastline is represented by water in the land cover data. Since land cover is not considered in this case study the complex shape of the wharf is not found. Hence, this area cannot be found by either the threshold or cluster method.

In Figure 9 and 10 the areas identified as hard to read in the user test are symbolized with a thick line (red), areas identified by the threshold method are bright (green), and areas identified by the cluster method are dark (green). In Figure 9 all data layers except contours and land cover are considered and settings for the cluster method are as in Table 1, Figure 7. The threshold method identifies all areas from the user test except a small part of one area in the North-East part. However, large areas that were not perceived as hard to read in the user test are included. The cluster method fails to identify larger portions of the areas that were perceived as difficult to read in the user test, and three small are totally missed. However, substantially fewer areas that were not perceived as difficult to read in the user test are

identified as difficult to read by the cluster method.

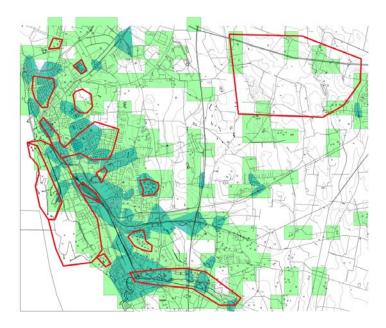
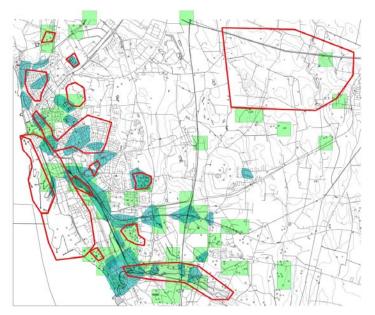


Figure 9. Comparison of areas of the map that are hard to read identified by (light green) the threshold method and by (dark green) the cluster method (settings as in Table 1 – Figure 7). All data except contour lines and land cover are used.

In Figure 10 contour lines and land cover are excluded from the test. For the threshold method also roads are excluded. For the cluster method settings are as in Table 1, Figure 8. In this test the threshold method identifies fewer areas, but it also fails to identify several areas that are hard to read according to the user test. The cluster method also identifies fewer areas compared to Figure 9; however, nearly the same result as for the test in Figure 9 is reached for areas that are hard to read according to the user test.



*Figure 10.* Comparison of areas of the map that are hard to read identified by (light green) the threshold method and by (dark green) the cluster method (settings as in Table 1 – Figure

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# 8). All data except contour lines and land cover are used – for the threshold method also roads are excluded.

In Figure 10 the threshold method mainly fails to identify areas with several roads which is natural since roads are not considered in the test. The major concern for the cluster method is the point objects as discussed earlier. This situation is likely possible to improve by adding a higher number of map points for point objects. By adjusting the parameters *minPts* and  $\varepsilon$  for DBSCAN more areas would be identified as difficult to read. However, identifying more areas will inevitably include more areas that are not perceived as hard to read. These conflicting aspects must be considered if the method is further developed.

## 8. Discussion

The main aim of the threshold and cluster methods is to identify areas in a map that are difficult to read as part of the generalization process. The outcome of the methods should guide the generalization process by identifying which areas that most likely requires generalization. Figure 11 shows an example of how the threshold and/or cluster methods can be used in a *legibility service*. The service is utilized to improve legibility when data from several web services are viewed in a geoportal. A user connects to a geoportal via the Internet and requests a map that consists of geographic data from several external services. Since both the threshold and cluster methods require the geographic data, these external services must be download services, such as *Web Feature Service* (WFS) that enables a user to download the data. The geoportal retrieves the data requested and sends them to the legibility service. The legibility service identifies areas that are difficult to read, and applies generalization operations to enhance legibility. Finally a map is created from the generalized data and returned to the user.

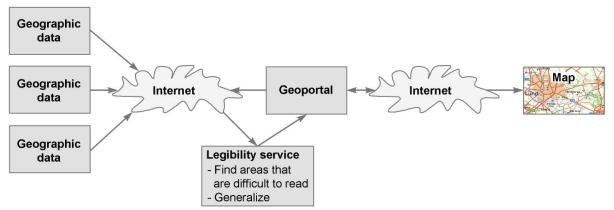


Figure 11. A possible future implementation of the threshold and/or cluster methods as a legibility service to improve legibility when a map is viewed in a geoportal.

How a legibility service identifies areas that are difficult to read in an efficient manner can be discussed. A major difference between the threshold method and the cluster method is that the threshold method considers several measures that are based on empirical studies. This implies that it is likely to identify areas that are hard to read with a higher accuracy. However, the cluster method by far outperforms the threshold method in time efficiency. A possible approach would be to apply the cluster method on the original data to find a candidate set of areas with poor legibility. The threshold method could then be applied to perform a refined search on the candidate set. Finally, generalization operations are applied on the areas

identified as difficult to read. However, performance must be considered. It might be so that it is more efficient to apply generalization directly on the areas identified by the cluster method, than first refining the search with the threshold method.

As a future extension it might also be possible to extend the legibility service to play the role of a virtual cartographer. A possible workflow would be:

- 1. Find areas with poor legibility
- 2. Apply appropriate generalization operations on these areas (if any).
- 3. Apply symbolization methods to improve cartography.
- 4. Apply text placement methods.

## 9. Conclusions

Based on the studies in this paper we can draw the following conclusions:

\* Both the threshold method and the cluster method are able to identify most of the areas in the map that are difficult to read (as stated in the user test) where the difficulties stem from cluttering. There are also other reasons for an area to be perceived as difficult to read, such as the symbology used. Areas that are perceived as hard to read due to these reasons are not identified by the methods tested.

\* The threshold method is advantageous in the sense that it is built on empirical studies of map reading. This in contrast to the cluster method, which is a method selected by intuition that it should provide a good result. On the other hand, the cluster method is much more efficient and could be utilised in a real-time process. For that reason it is interesting that the cluster method almost provides the same result as the threshold method (cf. Figure 9 and 10). We believe that with some effort in tailoring the cluster method it could be a proper alternative to the more empirically solid threshold method.

#### Acknowledgements

We would like to thank all the participants in the user tests. Lantmäteriet and the city of Helsingborg are acknowledged for providing geographic data.

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